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Forecast-Based Uncertainty and Risk Analysis of Major Cereal Production in Tamil Nadu

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Abstract

Reliable cereal production forecasting is essential for effective agricultural planning; however, point forecasts alone do not adequately capture the uncertainty associated with future output. This study evaluates forecast uncertainty and production risk across major cereals using forecast-derived measures rather than model re-estimation. Forecasted production values for paddy, sorghum, pearl millet, finger millet, and maize over the period 2025–2029 were analysed using prediction interval–based indicators and dispersion measures. Forecast uncertainty was quantified through the width of prediction intervals and relative uncertainty measures, while production risk was assessed using the coefficient of variation and a composite risk index. The results reveal substantial variation in forecast-induced risk across cereals. Paddy and maize exhibit relatively stable forecasted production with low variability and risk indices, indicating lower exposure to uncertainty. In contrast, pearl millet and sorghum show higher relative uncertainty and elevated risk levels, reflecting greater vulnerability to production fluctuations. Finger millet displays moderate risk characteristics. The findings demonstrate that cereals differ markedly in their exposure to forecast uncertainty, largely due to variability in cultivated area and production scale. By emphasizing uncertainty-aware evaluation, the study provides a practical framework for comparing cereals under risk and supports informed, crop-specific policy interventions aimed at enhancing resilience in cereal production systems.

Key words: Forecast uncertainty; Production risk; Cereal production; Prediction intervals; Risk index; Coefficient of variation; Agricultural planning

1. Introduction

Cereal production plays a vital role in ensuring food security, agricultural sustainability, and effective policy planning, particularly in regions where staple crops such as paddy, sorghum, pearl millet, finger millet, and maize constitute a significant share of total agricultural output. Stability in cereal production is essential for procurement planning, buffer stock management, and price stabilization. However, agricultural production systems are inherently subject to uncertainty due to fluctuations in cultivated area, climatic variability, and structural changes in farming practices. These factors introduce considerable challenges in forward-looking agricultural decision-making and long-term planning. Previous studies, including those by David B. Lobell et al. (2011) and Reto Knutti et al. (2010) have demonstrated that climate variability and model uncertainty significantly influence crop production patterns, thereby complicating reliable forecasting and risk assessment.

Forecasting future cereal production is widely used as a tool to support agricultural planning by providing advance estimates of expected output levels. In many cases, production dynamics are influenced not only by historical trends but also by structural factors such as the area under cultivation. Forecasting approaches that incorporate such exogenous variables, including ARIMAX-type models, are therefore particularly useful for generating crop-wise production forecasts. The present study utilizes forecasted production values for major cereals—paddy, sorghum, pearl millet, finger millet, and maize—obtained through such a modelling framework. The forecasted production values used in this study were generated in an earlier phase of the present research using an ARIMAX modelling framework, incorporating area under cultivation as an exogenous variable. While the earlier phase focused on model development and forecasting performance, the present study extends the analysis by evaluating forecast uncertainty and production risk based on forecast-derived measures. As emphasized by Rob J. Hyndman and George Athanasopoulos (2018), the inclusion of explanatory variables along with the estimation of prediction intervals enhances the robustness and interpretability of time series forecasts in applied contexts such as agriculture.

Despite the widespread use of forecasting models, the interpretation of results often relies heavily on point estimates, which provide only limited information about the uncertainty associated with future production. Agricultural planning based solely on expected values may underestimate potential deviations arising from inherent variability, especially when comparing cereals with differing production characteristics. To address this limitation, the present study emphasizes the importance of incorporating forecast uncertainty into production analysis. Prediction intervals associated with forecasted values offer a practical means of quantifying uncertainty by specifying the range within which future production is likely to vary. Furthermore, the use of dispersion-based measures such as forecast range, coefficient of variation, and composite risk indices enables a systematic assessment of production risk across different cereals. This approach is consistent with the probabilistic forecasting framework highlighted by Tilmann Gneiting and Matthias Katzfuss (2014), which underscores the importance of uncertainty quantification in improving decision-making under risk.

Although cereal production forecasts are frequently generated, the associated uncertainty and risk are often not adequately examined, thereby limiting their practical utility in agricultural planning and policy formulation. In this context, the present study seeks to bridge this gap by focusing on the assessment of forecast uncertainty and production risk using forecast-derived measures, rather than solely emphasizing forecasting methodology. By linking expected production outcomes with their associated variability, the study aims to provide a more comprehensive and risk-informed perspective for agricultural decision-making.

Accordingly, the study utilized forecasted production values for paddy, sorghum, pearl millet, finger millet, and maize to evaluate forecast uncertainty and production risk. The objectives of the study were to:

1. quantify forecast uncertainty in cereal production using prediction interval–based measures;
2. assess production risk across cereals using dispersion-based indicators; and
3. compare major cereals based on their forecast-induced risk levels.

2. Review of Literature

Gao Gao, Kwoklun Lo, and Jianfeng Lu (2017) examined electricity price volatility in the UK electricity market by examining forecast uncertainty as a major source of market risk. Using ARIMA and Artificial Neural Network (ANN) models, they identified high-risk periods across different time horizons. Forecast uncertainty was measured through a risk index derived from short-term forecasting errors, with risk assessed on daily and seasonal bases. The study also distinguished between weekday and weekend price profiles to capture variations in electricity price dynamics.

WenJun Zhang et al. (2011) analyzed long-term global production trends of cereals, paddy rice, wheat, fruits, and vegetables using GLM models. It provided forecasts up to 2030 and highlighted regional disparities in crop dominance. The authors emphasized uncertainty in production patterns due to socio-economic and environmental factors and suggested that probabilistic forecasting is essential for improving food security planning and policy decisions.

David B. Lobell et al. (2011) investigated the relationship between climate variability and crop yields across major regions. It revealed that temperature increases and rainfall variability introduce significant uncertainty in yield forecasts, particularly for wheat and maize. The findings stressed the importance of incorporating climatic uncertainty into forecasting models to improve agricultural risk assessment.

Reto Knutti et al. (2010) discussed methodological issues in combining outputs from multiple climate models and quantified the uncertainty arising from model differences. It highlighted that such uncertainty directly affects agricultural forecasts and risk evaluations, suggesting ensemble approaches for more robust predictions.

Christopher B. Field et al. (2014) IPCC report provided a comprehensive assessment of climate change impacts on agriculture, emphasizing uncertainty in future crop productivity. It highlighted risks related to extreme weather events and suggested adaptive forecasting strategies to minimize agricultural losses.

Pierre Pinson (2013) introduced probabilistic forecasting frameworks that quantify uncertainty using prediction intervals and density forecasts. Though applied to energy systems, the methodology is highly relevant for agricultural forecasting, particularly in modeling uncertain yield and production patterns.

Paweł Ziemba et al. (2021) integrated fuzzy logic with forecasting models to handle ambiguity and incomplete data. It demonstrated that uncertainty-aware decision-making frameworks improve risk evaluation, which can be effectively applied to agricultural production systems under uncertain environmental conditions.

Rob J. Hyndman and George Athanasopoulos (2018) provided a comprehensive framework for time series forecasting, including ARIMA models and prediction intervals. It emphasized the importance of measuring forecast uncertainty through confidence intervals, which is crucial in crop yield prediction and agricultural planning.

Tim Bollerslev (1986) introduced GARCH models to capture time-varying volatility in data. It is particularly useful in modeling uncertainty in agricultural price and production series, enabling better risk estimation under fluctuating conditions.

James H. Stock and Mark W. Watson (2007) analyzed increasing forecast uncertainty due to structural changes in economic systems. The concepts are applicable to agriculture, where market dynamics and policy changes introduce additional uncertainty in production and price forecasting.

3. Data Source

The analysis is based on forecasted cereal production values generated for major cereals, namely paddy, sorghum, pearl millet, finger millet, and maize. The forecasted values were obtained from previously estimated time-series forecasting models that incorporate cultivated area as an external influencing factor. These forecasts provide expected production levels along with associated prediction intervals, which form the basis for assessing forecast uncertainty and production risk.

The forecast horizon considered in the study covers a five-year period from 2025 to 2029. For each cereal, year-wise forecasted production values and their corresponding lower and upper confidence limits were compiled and organized into a structured dataset. The study utilizes only forecast-derived information and does not involve re-estimation of forecasting models or the use of raw historical production data.

By focusing exclusively on forecast outputs, the data framework supports a consistent and comparable assessment of uncertainty and risk across cereals, enabling meaningful evaluation of forecast-induced variability in future production.

4. Methodology

The study employs forecast-derived measures to evaluate uncertainty and production risk across cereal crops. All measures are computed using forecast outputs and associated prediction intervals rather than by re-estimating forecasting models.

4.1. Forecast Uncertainty Measures

Forecast uncertainty is quantified using prediction intervals around forecasted production values. A prediction interval provides a range within which future observations are expected to lie at a given confidence level, and is widely used in forecasting evaluation (Hyndman & Athanasopoulos, 2018).

The Forecast Range (FR) measures the width of the prediction interval:

$$\text{Forecast Range (FR)} = \text{UCL}_\alpha - \text{LCL}_\alpha \quad (1)$$

where UCL_α and LCL_α are the upper and lower confidence limits at confidence level α, respectively (Hyndman & Athanasopoulos, 2018).

To facilitate comparison across cereals with varying production scales, Relative Forecast Uncertainty (RFU) is defined as the forecast range relative to the forecasted mean:

$$\text{Relative Forecast Uncertainty (RFU)} = \frac{\text{UCL}_\alpha - \text{LCL}_\alpha}{\text{Forecast}} \quad (2)$$

This normalizes the uncertainty measure, making it comparable across crops with different production magnitudes (Chatfield, 2004).

4.2. Risk Indicators

Production risk is assessed using dispersion measures derived from the distribution of forecasted values over the forecast horizon.

The Coefficient of Variation (CV) quantifies relative variability of forecasts:

$$\text{CV} = \frac{\sigma_{\text{Forecast}}}{\mu_{\text{Forecast}}} \times 100 \quad (3)$$

where σ_{Forecast} and μ_{Forecast} are the standard deviation and mean of forecasted values, respectively. CV is a dimensionless measure of variability widely used in statistical and agricultural research to compare relative risk across datasets (Everitt & Skrondal, 2010).

In addition, a Risk Index (RI) is computed to integrate forecast uncertainty with scale of production:

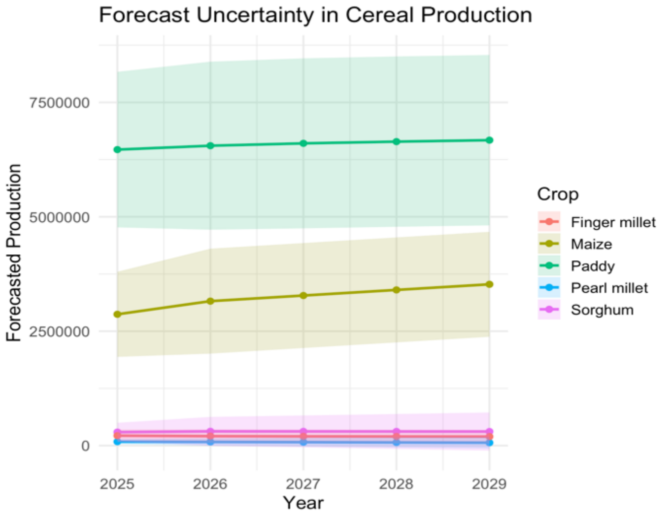
$$\text{Risk Index (RI)} = \frac{\text{Mean Range}}{\mu_{\text{Forecast}}} \quad (4)$$

Mean Range is the average of forecast ranges over the forecast horizon. This index captures both the magnitude of uncertainty and the expected production level, facilitating comparative risk assessment across different cereals (Frees, 1995).

5. Results and Discussion

Figure I. Forecast Uncertainty in Cereal Production (2025–2029)

The figure illustrates forecasted production trajectories for paddy, maize, sorghum, pearl millet, and finger millet over the period 2025–2029



The figure I reveals noticeable variation in forecast uncertainty across cereals over the forecast horizon. Paddy exhibits the highest forecasted production levels, accompanied by a relatively wider uncertainty band, indicating greater absolute variability in future output. Maize shows a moderate but steadily increasing production trend with a comparatively consistent uncertainty range, suggesting stable yet non-negligible production risk. In contrast, sorghum, pearl millet, and finger millet display lower forecasted production levels with narrower uncertainty bands, reflecting relatively lower absolute uncertainty. However, when considered in relation to their production scale, these crops may still be subject to meaningful relative risk. Overall, the results highlight that cereals differ substantially in their forecast-induced uncertainty, emphasizing the need for crop-specific risk assessment rather than reliance on point forecasts alone.

Risk Assessment

Table I presents a consolidated summary of forecast uncertainty and production risk measures for major cereals based on forecasted production values. The table reports mean forecast levels, average prediction interval width (mean range), variability of forecasts measured through standard deviation and coefficient of variation, and a composite risk index derived from forecast uncertainty. Based on the magnitude of the risk index, cereals are classified into qualitative risk levels, and a relative risk ranking is assigned, where a lower rank indicates higher forecast-induced production risk. This integrated presentation enables direct comparison of uncertainty and risk across cereals within a unified framework.

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Table 1: Comparative Risk Profile and Ranking of Major Cereals Based on Forecast Uncertainty

Crop	Mean Forecast	Mean Range	SD Forecast	CV Percent	Risk Index	Risk Level	Risk Rank
Finger Millet	205309	288063	8075	3.93	1.40	Low Risk	3
Maize	3247305	2205771	251563	7.75	0.679	Low Risk	4
Paddy	6589075	3645164	81049	1.23	0.553	Low Risk	5
Pearl Millet	75660	185339	8637	11.4	2.45	Moderate Risk	1
Sorghum	307444	665918	6964	2.27	2.17	Low Risk	2

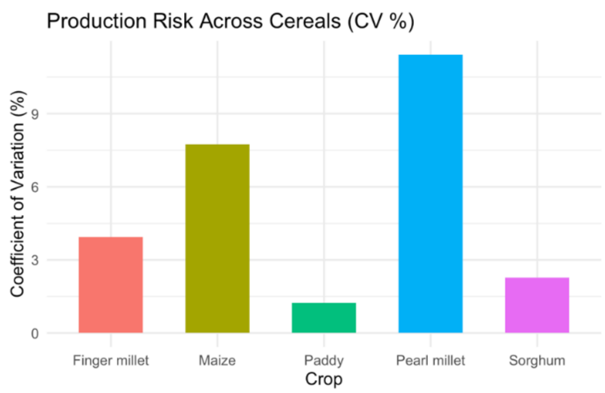
Interpretation of Forecast Uncertainty and Production Risk Across Cereals:

The results summarized in Table X reveal clear differences in forecast-induced production risk across cereals. Pearl millet exhibits the highest level of uncertainty relative to its forecasted production, as reflected by the highest coefficient of variation and risk index, placing it in the moderate-risk category. Sorghum and finger millet display moderate variability, indicating noticeable but comparatively lower production risk. Maize shows moderate dispersion in forecast values, while paddy records the lowest coefficient of variation and risk index, suggesting relatively stable future production prospects. Overall, the findings indicate that smaller cereals tend to face higher relative forecast uncertainty despite lower absolute production levels, emphasizing the importance of incorporating uncertainty-based measures rather than relying solely on mean forecasts.

Comparative Risk Ranking of Major Cereals Based on Forecast Uncertainty:

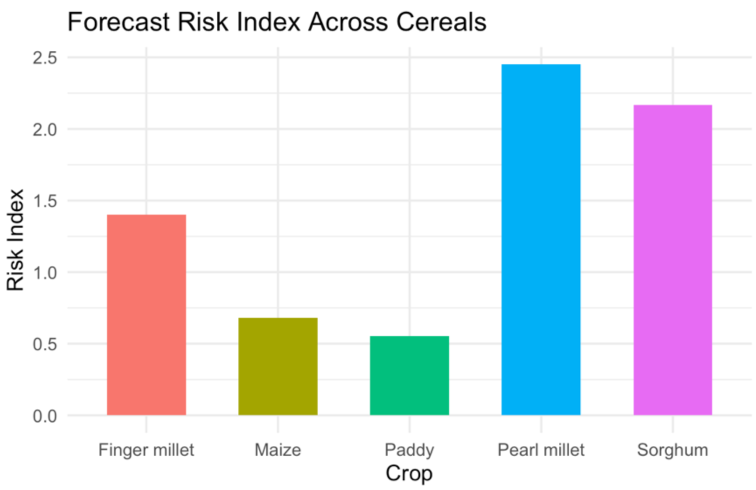
The risk ranking highlights substantial variation in forecast-induced risk among cereals. Pearl millet emerges as the most risk-prone cereal, followed by sorghum and finger millet, while maize occupies an intermediate position. Paddy ranks lowest in terms of forecast-induced risk, reflecting its comparatively stable production outlook. This ranking underscores the need for crop-specific risk management strategies, as cereals differ not only in production scale but also in the degree of uncertainty surrounding their future output. The results reinforce the value of ranking-based assessment for prioritizing policy attention and resource allocation in cereal production planning.

Figure 2: Comparative Production Risk Across Cereals Based on Coefficient of Variation (%)



The coefficient of variation highlights substantial differences in forecast-induced production risk across cereals. Pearl millet exhibits the highest CV, indicating the greatest relative variability in forecasted production and, consequently, the highest production risk among the cereals considered. Maize also shows notable variability, suggesting moderate production risk over the forecast horizon. In contrast, paddy records the lowest CV, reflecting comparatively stable and less uncertain future production. Sorghum and finger millet occupy intermediate positions, with moderate levels of variability. These results indicate that cereals with smaller production scales tend to experience higher relative uncertainty, underscoring the importance of evaluating production risk using relative dispersion measures rather than absolute forecast levels alone.

Figure 3: Risk Index–Based Comparison of Forecast-Induced Production Risk Across Cereals



The risk index highlights marked differences in forecast-induced production risk among cereals. Pearl millet records the highest risk index, indicating that forecast uncertainty is large relative to its expected production level, thereby making it the most vulnerable cereal in terms of future production stability. Sorghum also exhibits a high risk index, reflecting substantial uncertainty relative to its forecast mean. Finger millet shows moderate risk, while maize displays comparatively lower risk levels. Paddy registers the lowest risk index, suggesting that its forecasted production is relatively stable and less exposed to uncertainty. Overall, the results demonstrate that cereals with smaller production bases tend to face higher relative forecast risk, reinforcing the importance of risk-based evaluation alongside conventional forecast analysis.

Comparative Stability and Vulnerability of Cereals

The comparative assessment of forecast uncertainty and risk indicators highlights clear differences in production stability across cereals. Paddy exhibits the highest stability, reflected by the lowest coefficient of variation and risk index, indicating relatively consistent future production. Maize also demonstrates comparatively low forecast-induced risk, suggesting moderate stability over the forecast horizon.

In contrast, pearl millet emerges as the most vulnerable cereal, followed by sorghum, both showing high relative uncertainty and elevated risk indices. Finger millet occupies an intermediate position. These differences are largely attributable to variability in cultivated area, as cereals with more fluctuating or limited area under cultivation tend to experience greater forecast uncertainty. The results emphasize the need for crop-specific risk assessment when interpreting production forecasts.

Policy Implications

- High-risk cereals (pearl millet and sorghum) exhibit high forecast uncertainty and require priority attention through buffer stock policies, crop insurance coverage, and risk-mitigation mechanisms to protect farmers from production instability.
- Moderate-risk cereals (finger millet) need targeted stabilization measures, including improved access to inputs and extension services, to reduce variability in cultivated area and output.
- Low-risk cereals (paddy and maize) show relatively stable forecasted production and are suitable for planned production expansion, long-term procurement, and market-oriented development strategies.
- The findings emphasize the importance of planning under uncertainty, highlighting the need to integrate forecast-based risk indicators into agricultural policy formulation rather than relying solely on point forecasts.

6. Conclusion

This study assessed forecast uncertainty and production risk across major cereals using forecast-derived measures rather than relying solely on point forecasts. The results reveal substantial variation in forecast-induced risk among cereals, underscoring the importance of incorporating uncertainty-based indicators into cereal production analysis. Paddy and maize exhibit relatively stable forecasted production, characterized by low coefficients of variation and risk indices, indicating lower exposure to future production uncertainty. In contrast, pearl millet and sorghum display higher relative variability and risk, highlighting their greater vulnerability to forecast uncertainty, while finger millet occupies an intermediate position.

The findings demonstrate that cereals with smaller production bases and greater variability in cultivated area tend to experience higher relative forecast risk. By integrating prediction interval–based measures with dispersion indicators, the study provides a practical framework for comparing cereals under uncertainty. The approach enhances the relevance of forecasting exercises for agricultural planning and policy formulation by moving beyond average forecasts to explicitly account for production risk. Overall, the results support the adoption of uncertainty-aware forecasting frameworks to improve decision-making and resilience in cereal production systems.

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Reference:

[1] Li, X., Zhang, Y., & Wang, J. (2023). Forecasting agricultural production under climate uncertainty using machine learning techniques. Agricultural Systems, 205, 103567.
[2] Ray, D. K., Mueller, N. D., West, P. C., & Foley, J. A. (2022). Yield trends are insufficient to double global crop production by 2050. PLOS ONE, 17(6), e0268319.
[3] Zhao, C., Liu, B., Piao, S., Wang, X., Lobell, D. B., Huang, Y., et al. (2021). Temperature increase reduces global yields of major crops. Proceedings of the National Academy of Sciences, 118(9), e2010087118.

[4] Ziemba, P., Wątróbski, J., & Zioło, M. (2021). Energy security assessment using a fuzzy multi-criteria decision analysis approach. Energies, 14(18), 5934.
[5] Tack, J., Barkley, A., & Nalley, L. L. (2020). Effect of warming temperatures on U.S. wheat yields. Proceedings of the National Academy of Sciences, 117(29), 16861–16866.
[6] Gao, G., Lo, K., & Lu, J. (2017, August). Risk assessment due to electricity price forecast uncertainty in UK electricity market. In 2017 52nd international universities power engineering conference (UPEC) (pp. 1-6). IEEE.
[7] Pagano, G., Li, H., & Thompson, M. (2019). Ensemble forecasting and uncertainty quantification in agricultural systems. Environmental Modelling & Software, 119, 276–288.
[8] Hyndman, R. J., & Athanasopoulos, G. (2018). Forecasting: Principles and practice (2nd ed.). OTexts.
[9] Rob J. Hyndman, R. J., & George Athanasopoulos, G. (2018). Forecasting: Principles and practice (2nd ed.). OTexts. https://otexts.com/fpp2/
[10] Gneiting, T., & Katzfuss, M. (2014). Probabilistic forecasting. Annual Review of Statistics and Its Application, 1, 125–151.
[11] Field, C. B., Barros, V. R., Dokken, D. J., Mach, K. J., Mastrandrea, M. D., Bilir, T. E., et al. (2014). Climate change 2014: Impacts, adaptation, and vulnerability. Cambridge University Press.
[12] Ross, S. M. (2014). Introduction to probability models (11th ed.). Academic Press.
[13] Tilmann Gneiting, T., & Matthias Katzfuss, M. (2014). Probabilistic forecasting. Annual Review of Statistics and Its Application, 1, 125–151. https://doi.org/10.1146/annurev-statistics-062713-085831
[14] Pinson, P. (2013). Wind energy: Forecasting challenges for its operational management. Statistical Science, 28(4), 564–585.
[15] Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate trends and global crop production since 1980. Science, 333(6042), 616–620.
[16] Zhang, W., Liu, G., & Bai, C. (2011). A forecast analysis on global production of staple crops.
[17] Knutti, R., Furrer, R., Tebaldi, C., Cermak, J., & Meehl, G. A. (2010). Challenges in combining projections from multiple climate models. Journal of Climate, 23(10), 2739–2758.
[18] Reto Knutti, R., Furrer, R., Tebaldi, C., Cermak, J., & Meehl, G. A. (2010). Challenges in combining projections from multiple climate models. Journal of Climate, 23(10), 2739–2758. https://doi.org/10.1175/2009JCLI3361.1
[19] Stock, J. H., & Watson, M. W. (2007). Why has U.S. inflation become harder to forecast? Journal of Money, Credit and Banking, 39(s1), 3–33.
[20] Jorion, P. (2007). Value at risk: The new benchmark for managing financial risk (3rd ed.). McGraw-Hill.
[21] Chatfield, C. (2000). Time-series forecasting. Chapman & Hall/CRC.
[22] Levin, A., Wieland, V., & Williams, J. C. (2003). The performance of forecast-based monetary policy rules under model uncertainty. American Economic Review, 93(3), 622-645.
[23] Hamilton, J. D. (1994). Time series analysis. Princeton University Press.
[24] Cooke, R. M. (1991). Experts in uncertainty: Opinion and subjective probability in science. Oxford University Press.
[25] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307–327.